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Fusion-based surveillance WSN deployment using Dempster–Shafer theory

Mustapha Reda Senouci [a], Abdelhamid Mellouk [b,*], Nadjib Aitsaadi [b], Latifa Oukhellou [c]

[a] A.I. Laboratory, Ecole Militaire Polytechnique, P.O. Box 17, Bordj-El-Bahri 16111, Algiers, Algeria
[b] LiSSi Laboratory, Department of Networks and Telecoms, University of Paris-Est Creteil (UPEC), France
[c] UPE, IFSTTAR, GRETTIA, Marne-la-vallée, France

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ABSTRACT

In mission-critical Wireless Sensor Networks surveillance applications, a high detection rate coupled with a low false alarm rate is essential. Additionally, fusion methods can be employed with the hope that aggregation of uncertain information from multiple sensors enhances the quality of surveillance provided by the network. This paper investigates the following fundamental problem: what is the best way to deploy a finite number of unreliable sensors characterized by uncertain readings in order to satisfy the user detection requirements. Unlike prior efforts that rely on simple fusion schemes, we use the Dempster–Shafer theory to define a generic evidence fusion scheme that captures several characteristics of real-world applications. The fusion-based uncertainty-aware sensor networks deployment problem is formulated as a binary non-linear and non-convex optimization problem that is NP-hard, and an efficient heuristic using genetic algorithms is investigated. The effectiveness and efficiency of the proposed approach are evaluated using both simulations and experiments. The obtained results demonstrate the appropriateness of the evidence fusion model that considers in a meaningful way the information on the quality of sensors decisions as well as the reliability of these sensors along with their uncertain and imprecise decisions. Also, the proposed approach outperforms state-of-the-art deployment strategies.

1. Introduction

A Wireless Sensor Network (WSN) is a network of wirelessly connected small-scale, low-power, low-cost devices called sensor nodes (or sensors). These tiny sensors are equipped with sensing, computation, storage, communication, and power.

Critical applications such as military target detection impose stringent requirements for event detection accuracy such as a low false alarm rate coupled with a high detection rate. To detect a target, the sensors have to make local observations of their surrounding environment and collaborate to produce a global decision that reflects the status of the Region of Interest (RoI). It is well known that collaboration among sensors improve the sensing quality by jointly considering noisy measurements of multiple unreliable sensors. For example, He et al. (2006) show that the false alarm rate of a real-world Mica2 WSN can be reduced from 60% (when sensors decide independently) to near zero by adopting a fusion scheme.

The deployment is a mandatory and critical step in the process of developing WSNs solutions for real-life applications. Even if many optimizations can be done once the WSN is deployed to enhance its performance, we believe that the most important optimization steps are those performed at the design step in order to build the best possible topology that meets specific user requirements.

Deploying WSNs into the real-world could be a very challenging task. Actually, in addition to the intrinsic properties of WSNs, many challenges stem from the close interactions between the WSN and the physical environment. Examples of such challenges include:

- How to consider uncertainty related to sensors readings?
- How to consider sensor reliability?
- How to combine sensory data from multiple sensors that can vary in their reliability?
- How to consider harsh deployment environments?

By considering such fundamental challenges in the early design steps of the WSN, one can avoid unpleasant surprises and save effort, time, and money. In an attempt to handle the challenges above, the present paper brings the following contributions:

1. A formal definition of an evidence-based sensing model is provided on the basis of Dempster–Shafer theory (Smets and

* Corresponding author. Tel.: +33 141807313; fax: +33 141807376.
E-mail addresses: mrsenouci@gmail.com (M.R. Senouci), mellouk@u-pec.fr (A. Mellouk), aitsaadi@u-pec.fr (N. Aitsaadi), latifa.oukhellou@ifsttar.fr (L. Oukhellou).

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Kennes, 1994). The proposed model captures several characteristics of real-world applications.
2. To build belief functions from raw sensing data, a two-step method is described.
3. The *fusion-based uncertainty-aware sensor networks deployment* (denoted by FUSD) problem is formulated as a binary non-linear and non-convex optimization problem. Several characteristics of real-world applications including sensor's spatial distribution, uncertain sensor measurements, challenging environments, and sensor reliability can be captured in this framework.
4. An efficient heuristic for the FUSD problem is developed. The effectiveness and efficiency of the proposed approach are validated through extensive experiments carried out on both synthetic dataset, data traces collected from a military vehicle detection experiment, as well as a lab testbed.

The remainder of this paper is organized as follows. Section 2 reviews related work. The background of the present work is described in Section 3. Section 4 defines our evidence fusion model. In Section 5, the FUSD problem is formalized. Section 6 addresses our sensor placement algorithm. The evaluation of our proposed approach via numerical experiments and trace-driven simulations is presented in Section 7. Section 8 discusses the results obtained by deploying an experimental testbed for motion detection. In Section 9, some possible extensions are presented. Section 10 concludes the paper and discusses some future directions for our work.

2. Related work

In our previous work (Senouci et al., 2015), we have investigated the belief functions theory (Smets and Kennes, 1994) to design a unified approach for the uncertainty-aware WSNs deterministic deployment. However, the devised approach considers only the rate of coverage and ignores completely the issue of false alarm. Hence, generated topologies do not guarantee the false alarm rate. In contrast to our previous work (Senouci et al., 2015), in this work we consider both false alarm and detection requirements.

A viable approach to meet false alarm requirements is data fusion. Two common fusion schemes are considered in the literature: the value fusion and the decision fusion schemes (Varshney, 1996). In the first one, the nodes exchange their raw energy measurements whereas in the second scheme the nodes exchange local detection decisions based on their energy measurement. Value and decision fusion were compared in Clouqueur et al. (2003, 2004). In Clouqueur et al. (2003), it was found that the former performs better in terms of detection probability for low noise levels; however, for noisy energy measurements decision fusion was proved more robust. Clouqueur et al. (2004) show that decision fusion become superior to value fusion as the ratio of faulty sensors to fault free sensors increases. Furthermore, the communication cost is lower in decision fusion than in value fusion.

As a compromise, an information-rich cost-effective approach is formulated in the present paper. An evidence could be transmitted to the fusion center containing uncertain decision along with the information quality related to the degree of confidence that a sensor has about its decision. This approach combines the advantages of both value and decision fusion approaches.

Chang et al. (2011) assume that targets appear at a set of known physical locations referred to as surveillance spots $T=\{t_j, 1\le j\le K\}$, where $t_j=(x_j,y_j)\in RoI$ is the coordinates of the jth spot. They also assume that only the sensors close to a surveillance spot participate in the data fusion. For any surveillance spot, the fusion region is a disk of radius R centered at the spot. Finally, they define the impact region of a surveillance spot as the disk of radius $2R$ centered at the spot. The fusion-based deployment problem is defined as follows: Given a RoI and a set of surveillance spots T, find a sensor placement $S=\{(x_i,y_i), 1\le i\le N\}$, such that the number of sensors $|S|$ is minimized subject to $\min_{1\le j\le K}\{P_{d_j}\}\ge\beta$, where P_{d_j} is the detection probability and β is the required minimum event detection probability threshold.

The straightforward optimal solution for the above problem, proposed by Chang et al. (2011), is to iterate incrementally N from 1 to search for the optimal sensor placement. In each iteration, $\min_{1\le j\le K}\{P_{d_j}\}$ is maximized. Once the constraint $\min_{1\le j\le K}\{P_{d_j}\}\ge\beta$ is satisfied, the global optimal solution is found. To solve the non-linear and non-convex optimization problem in each iteration, Chang et al. (2011) apply a non-linear programming solver based on the Constrained Simulated Annealing (CSA) algorithm (Wah et al., 2007), which is a global optimal algorithm that converges asymptotically to a constrained global optimum (Wah et al., 2007, Theorem 1). However, the complexity of CSA increases exponentially with respect to the number of variables (Wah et al., 2007). Therefore, for a large-scale deployment problem, the global optimal solution becomes prohibitively expensive.

Chang et al. (2011) also propose a relatively low computational cost Divide-and-Conquer (D&C) heuristic. In the divide step, for each surveillance spot t_j, they find the set of spots within the impact region of t_j. In the conquer step, for each surveillance spot t_j, the fewest additional sensors are placed within the fusion region of t_j to cover t_j and the neighboring spots in its impact region. The optimization is implemented by the aforementioned CSA solver.

Ababnah (2010) treated the deployment problem in the context of optimal control theory. Specifically, they model the deployment problem as a linear quadratic regulator problem, with the deployment locations serving as control parameters. Assuming a value fusion scheme and under several approximations, Ababnah and Natarajan (2009) try to linearize the formulation proposed in Chang et al. (2011) and solve the deployment problem as an optimal control problem. Within this framework, they propose a sequential sensor deployment algorithm whose computational complexity is equal to $O(3n^6+4n^4)$ for an $n\times n$ RoI. In a recent work, Ababnah and Natarajan (2010) introduced a similar algorithm while considering the majority or counting rule as a decision fusion rule. The computational complexity of the proposed algorithm is equal to $O(3n^6+4n^4)$. The aforementioned works are

Table 1
A comparison between various fusion-based deployment approaches.

Paper	Computational complexity	Fusion model	Primary objective	Secondary objective	Constraint
Ababnah and Natarajan (2009)	$O(3n^6+4n^4)$	Value fusion	Max. detection performance	–	Fixed number of sensors
Ababnah and Natarajan (2010)	$O(3n^6+4n^4)$	Decision fusion	Max. detection performance	–	Fixed number of sensors
Chang et al. (2011)	$O(e^{n^2})$	Value fusion	Max. detection performance	Min. the number of sensors	–
Chang et al. (2011)	$O(n^2me^m)$[a]	Value fusion	Max. detection performance	Min. the number of sensors	-

[a] m is the average number of spots in the impact region.